

INTRODUCTION

In the last decade, the number of research works published in the area of artificial olfaction has increased notably, with important advances in chemical sensor technology, bio-inspired and engineering based e-noses, and a broad range of algorithms to counteract drift and environmental cross-sensitivity, as well as to improve efficiency in the recognition of chemical volatiles. Likewise, a promising transfer from laboratories to real world applications has started, which despite the long and challenging road ahead, vows for granting this forgotten sense the importance it has in the animal kingdom (Doty, 2015).

In this regard, mobile robot olfaction (MRO), the branch of robotics that addresses the integration of gas and chemical sensors on-board mobile platforms, has also gained substantial relevance in the scientific community due to the interesting advantages a mobile robot brings when compared with the traditional approach based on networks of static e-noses (Tsujita, Yoshino, Ishida, & Moriizumi, 2005). First, a mobile robot usually carries only one e-nose, therefore a more sophisticated and powerful (and more expensive) model can be used, enabling the analysis of more complex compounds and the detection of faster changes in the gas concentration (Gonzalez-Jimenez, Monroy, Garcia, & Blanco, 2011; Ishida, Kobayashi, Nakamoto, & Moriizumi, 1999; Sanchez-Garrido, Monroy, & Gonzalez-Jimenez, 2014; Werle et al., 2002). The calibration phase of the sensing devices is greatly simplified because of the reduced number of e-noses, something that represents an important issue in large gas sensing networks (Esposito et al., 2016). Also, MRO systems permit sampling at higher (and adaptive) resolutions, while still providing the required accurate localization of each measurement. Finally, a mobile robot can leverage environmental information provided by other sensors on board (anemometers, cameras, laser scanners, etc.) to enhance the olfaction task, for example by detecting obstacles or changes in the environmental conditions, and to process such data in an online fashion, allowing decision making.

Three are the main fields where gas-sensitive mobile robots have been proposed: volatile chemical recognition, which deals with the problem of identifying which of a set of categories a new volatile sample belongs to, gas distribution mapping, where the objective is to obtain a truthful representation of how volatiles are dispersed in the inspected area and their respective concentrations, and gas source localization, where the robot is commanded to localize the emission sources. In this chapter, achievements made to each of these three fields are reviewed after a brief overview of the specific challenges of gas-sensitive mobile robots.

SPECIFIC CHALLENGES OF GAS-SENSITIVE MOBILE ROBOTS

The development of mobile robot olfaction systems is not a trivial problem, and despite recent achievements, the potential of gas-sensitive mobile robots has yet to be fully realized. Besides the inherent complexity of artificial olfaction, new difficulties emerge when performing olfaction with a mobile robot. In this section, a review of the main issues and technical solutions proposed so far is presented.

Chemical Sensors

While most animals, from simple bacteria to mammals, are empowered with a highly developed and sharp sense of smell, sensors for robots with capabilities close to those of animals are not yet available. One of their main drawbacks is related to the response speed. While the response time of an animal's chemoreceptor is in the order of 100ms (Beer & Ritzmann, 1993), typical gas sensors need several tens of

seconds before their responses reach the steady state values (Pearce, Schiffman, Nagle, & Gardner, 2006). For illustration, Figure 1 shows the rise and recovery times of a conventional metal oxide gas sensor when exposed to a rapid excitation. As reported in (Monroy, Gonzalez-Jimenez, & Blanco, 2012) the adopted solution to palliate this negative effect has been, in most cases, to slow down the locomotion of the robot to a few cm/s, as in (Ishida, Suetsugu, Nakamoto, & Moriizumi, 1994). Yet, over the past years, different hardware and software approaches have been proposed to overcome to a certain extent this important limitation (Di Lello, Trincavelli, Bruyninckx, & De Laet, 2014; Fonollosa, Sheik, Huerta, & Marco, 2015; Gonzalez-Jimenez, Monroy, & Blanco, 2011), enabling a higher speed for the robot and consequently improving its effectiveness in real world applications.

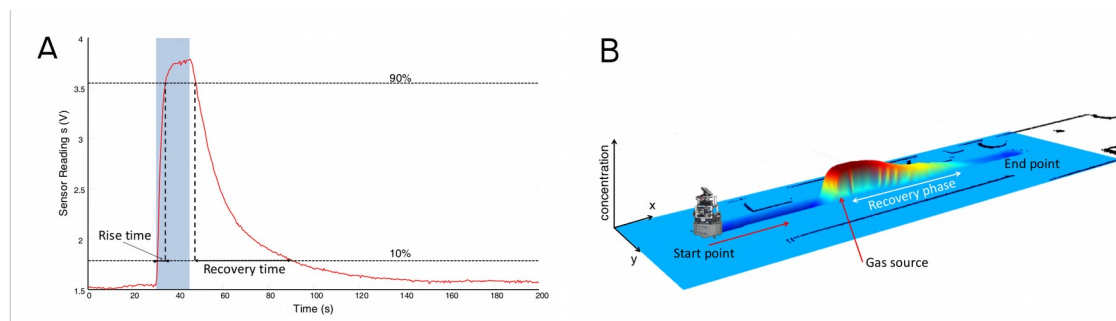


Figure 1. Rise and recovery phases of a metal oxide gas sensor response to a step gas concentration. (A) 2D plot of the sensor response over time, where the shaded-blue region denotes the sensor exposure to the analyte. (B) 3D gas distribution map generated from the readings of the gas sensor carried by a mobile robot along a corridor. It can be appreciated how the recovery phase after the gas exposure last for tens of seconds.

Slow sensor response also poses a significant challenge when performing volatile chemical discrimination. Gases disperse chaotically, led by turbulent advection, resulting in a concentration field that consists of fluctuating, intermittent patches of high gas concentration (Balkovsky & Shraiman, 2002). As a consequence, the sensor signals to be processed are noisy and dominated by the signal transient component. Patterns obtained are consequently distorted because sensors with different selectivities tend to have different response times (Schleif et al., 2016). Despite this, some recent works have addressed the issue, presenting different perspectives which will be latter covered in this book.

Absence of Ground Truth

In real, uncontrolled environments, both indoor and outdoor, the dispersion of gases is dominated by turbulent flows. A turbulent flow is that in which fluid particles move in a random and chaotic way within the flow field (Sklavounos & Rigas, 2004). Furthermore, environmental variables such as temperature, pressure or humidity, as well as the airflow disruptions caused by the own robot movement, also have an important impact in the gas dispersion. All this entails the impossibility to know the exact behavior of a volatile release, and consequently, to have a *ground truth* of the nature and concentration of the chemical volatiles. This undoubtedly represents one of the main drawbacks for conducting real experimentation, and usually forces researchers to consider semi-controlled scenarios from which ground truth estimations can be reasonable assumed (Monroy & Gonzalez-Jimenez, 2017).

To cope with this problem, simulation tools with the capacity to properly handle the gas dispersion phenomenon (e.g. based on computation fluid dynamics) can be used to perform extensive evaluations

before moving to experimental trials. While there exist a few implementations of robotics-oriented gas dispersion simulation frameworks, most of them consider simplified environments, are developed in outdated robotic software platforms or rely on expensive, external software packages (Cabrita, Sousa, & Marques, 2010; Monroy, Blanco, & Gonzalez-Jimenez, 2013; Pashami, Asadi, & Lilienthal, 2010). One exception is the newly developed GADEN simulator (Monroy, Hernandez-Bennetts, Fan, Lilienthal, & Gonzalez-Jimenez, 2017), an open source gas dispersion simulation framework aimed to mobile robotic olfaction applications. GADEN enables the simulation of gas dispersal in any 3D environment (including obstacles and realistic configurations), together with mobile robotic platforms and sensing devices (e.g. MOX sensors, anemometers, etc.). This framework is built upon the robot operating system (ROS), arguably, the most widespread robotics OS used in academia and industry.

Power Consumption, Weight and Size

A common characteristic of most current mobile robots is the fact that they run on batteries. This entails the problem of balancing power consumption, payload and runtime, which becomes paramount for unmanned aerial vehicles (UAVs). In this context, and far from the bulky and power-hungry laboratory sensing devices (e.g. mass spectrometers), e-nose designs tailored for mobile robots have been proposed (Aleixandre et al., 2008; Gonzalez-Jimenez et al., 2011; Sanchez-Garrido et al., 2014). These robotic-oriented e-noses, some of which are illustrated in Figure 2, seek reducing energy usage and weight, while maintaining a decent efficiency in the detection and characterization of the chemical volatiles. However, the precision and reliability of these systems is, in most cases, far from their laboratory counterparts.

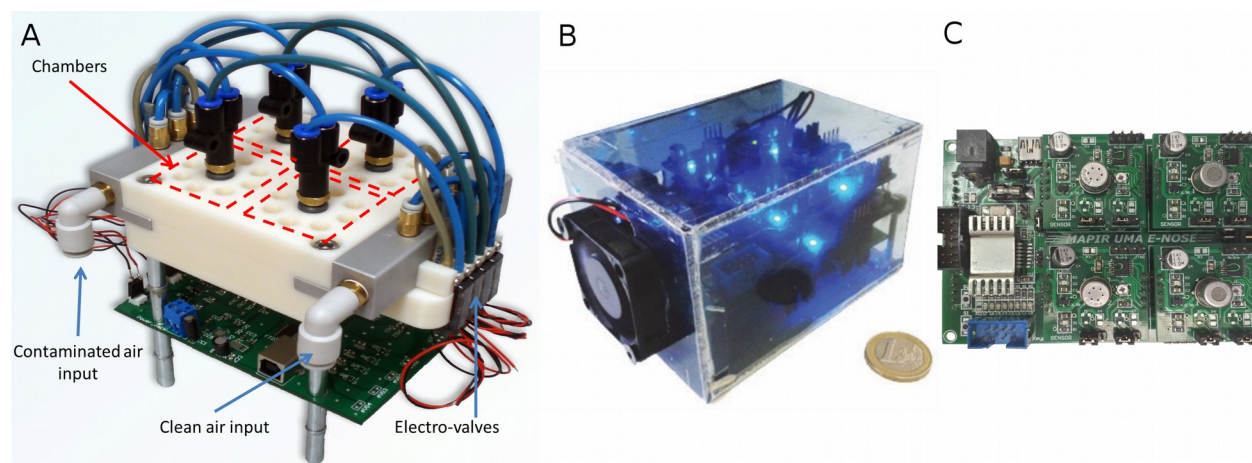


Figure 2. Pictures of two portable e-nose designs developed for mobile robotics. (A) The multi-chamber electronic nose - MCE-nose (Gonzalez-Jimenez et al., 2011), (B-C) prototype and detailed inspection of a modular e-nose containing eight smart gas detector modules (Sanchez-Garrido et al., 2014).

GAS CLASSIFICATION WITH MOBILE ROBOTS

The classification of volatile substances is, possibly, the most studied application of e-noses among the scientific community. It plays an important role for many industrial and medical applications including disease detection and diagnosis in medicine, quality control in food processing chains, finding drugs and explosives, or monitoring of pollution levels in air. Traditionally, this has been performed by analyzing the response of the array of gas sensors that compose the e-nose, when exposed to pulse-like gas excitations under well-controlled measurement conditions (i.e. temperature, humidity, exposure time, etc.) (Schaller, Bosset, & Escher, 1998; Vergara et al., 2012). Yet, from the variety of potential applications that may benefit from gas classification, some of them require to measure the environment continuously and at different locations. They include, among others, city odor mapping, pollution monitoring or leak detection. Mobile platforms can indeed contribute to this problem by trading off temporal coverage against spatial coverage, enabling a high spatial resolution across large areas without the need for a large number of sensing devices.

As mentioned previously, the discrimination of gases performed with a gas-sensitive robot presents a number of additional challenges when compared to standard analyte identification, mostly due to the differences in the measurement conditions and the fact that the sensor signals to be processed are noisy and dominated by the signal transient behavior. Most of the research in this direction has focused on three topics: impact analysis of the motion speed of the sensing device, study of which robot trajectory yields higher classification rates, and exploration of new feature sets to feed the pattern recognition algorithm. In this context, one of the first works was presented by Trincavelli and coauthors (Trincavelli, Lout, & Coradeschi, 2009), who used a robot carrying an e-nose and conducted a preliminary investigation on the most suitable path to optimize the classification accuracy, taking into account the possible effects of environmental variables on the signals collected along that path. The authors concluded that the movement strategy of the robot clearly affects the properties of the e-nose signals, therefore being possible to enhance the classification performance by optimizing the robot trajectory.

On this same topic, Monroy and Gonzalez-Jimenez (Monroy & Gonzalez-Jimenez, 2017) empirically analyzed the impact of the robot motion speed on the classification performance. The authors presented a large experimental dataset composed of 240 inspections of an indoor scenario, driving a mobile robot at four different speeds, under the presence of two gas sources. Two questions were addressed: (i) What is the relationship (if any) between the motion speed of an e-nose which is continuously sampling the environment and the classification accuracy?, and (ii) How must the classifier be trained to get the best possible performance?. The authors reaffirmed the conclusions from (Trincavelli et al., 2009), stating that an important deterioration in the classification performance (up to 30% in some of the configurations tested) was appreciated when the e-nose was sampling the environment in movement. Furthermore, they concluded that training the classifier with data collected at a few different motion speeds (from the range of possible velocities) should be enough to palliate this negative effect. Thus, and according to this study, training of the pattern recognition algorithm must be carried out with data collected in motion, in order to not deteriorate too much the classification performance.

An interesting work reaching similar conclusions is that presented by Vergara et al. (Vergara et al., 2013), which does not employ an e-nose in motion to gather the gas samples, but considers different wind velocities (which may be seen as the counterpart of moving the sensing device). The authors compiled an extensive dataset with nine static e-noses placed within a wind tunnel to evaluate the performance of several sensor arrays working in open sampling settings. Different locations of the e-noses, heater

voltages, wind speeds, and chemical volatiles compose the list of variables that make this dataset one of the most complete currently available. Particularly, two important conclusions were highlighted by the authors with regard to the wind speed: the classification performance was affected by the wind speed used during training, and that, in order to increase the robustness of the system against air flow variations, one may want to train the system at all the expected system conditions.

Naturally, not only the motion of the gas sensing device must be taken into account. As reported in (Trincavelli & Loutfi, 2010), the feature selection process is also of great importance. In this work the authors analyzed multiple features to determine those which are more robust to changes in the sampling trajectory and less dependent of the experimental setup. Two feature selection algorithms were proposed and compared to improve the performance of an olfactory robotic system. Experiments were performed in three different scenarios (two indoor and one outdoor) with four moving strategies, attempting to vary the interaction of the robot with a possible plume.

The classification of multiple volatile substances with an e-nose in motion is still an open and challenging research topic. Recent works keep proposing new feature selection algorithms and feature sets to enhance the performance, as in (Hernandez-Bennetts, Schaffernicht, & Pomareda-Ses, 2014) where the authors proposed to employ the sensor amplitude as an additional feature, or the application of statistical tools to exploit the temporal correlation of the e-nose data (Monroy & Gonzalez-Jimenez, 2015; Monroy, Palomo, Lopez-Rubio, & Gonzalez-Jimenez, 2016). Furthermore, like in the case of a network of fixed e-nose, the calibration and drift compensation of the sensors composing the e-nose is also an important drawback to consider. In this regard, works like (De Vito, Massera, Piga, Martinotto, & Di Francia, 2008; Esposito et al., 2016) have presented different approaches to cross-calibrate different e-noses without the need to perform a tedious and costly laboratory calibration. These proposals are indeed fundamental when the MRO system is to be deployed for long times (drift and ageing), or when multiple mobile e-noses are set up simultaneously (Hasenfratz, 2015).

Related to environmental monitoring applications, there are works where a gas measuring device sensing the air quality is carried by a person (Zappi, Bales, Park, Griswold, & Šimuni, 2012), a bike (Elen et al., 2013; Monroy, Gonzalez-Jimenez, & Sanchez-Garrido, 2014), public transport vehicles (Hasenfratz et al., 2015) or even drones (Neumann, Bartholmai, Schiller, Wiggerich, & Manolov, 2010; Pobkrut, Eamsa-ard, & Kerdcharoen, 2016). Despite sampling the environment in motion, most of the works does not perform a classification phase to discriminate the type of gas, but rather employs an array of gas sensors with disjoint selectivity (i.e. one sensor for each analyte to monitor, and usually discarding the cross-selectivity among classes). An interesting remaining question is whether the concentration measurements of the different pollutants can also be improved by taking into account the motion speed of the sensing device.

GAS DISTRIBUTION MAPPING

Gas distribution mapping (GDM) is the process of creating a representation of how gases spread in an environment from a set of spatially and temporally distributed measurements of relevant variables. Foremost, these measurements include the gas concentration itself, but may also comprise wind flow, pressure or temperature, among other representative variables.

Many gas distribution models were developed back in the early 90s to tackle atmospheric dispersion (Holmes & Morawska, 2006). These models estimate the distribution of airborne materials at the different

atmospheric-scales given a set of environmental and topographic conditions. Yet, such models are not suitable for local scales, not being designed to capture all the relevant aspects of gas propagation with a sufficient level of detail, as in the case of complex indoor and outdoor settings. Given that analytical solutions are intractable, it is then common practice to divide the space into a regular lattice of cells (gridmap), and then estimate a probability density function (pdf) of the gas concentration at each cell of the grid (see Figure 3). A crucial aspect when updating this gridmap is the fact that the majority of current e-noses are point sampling devices, that is, observations are only representative of the very near air around the e-nose. Moreover, given the ephemeral nature of gases (due to the mechanisms that rule gas dispersion (Shraiman & Siggia, 2000)), the information conveyed by a given measurement quickly vanishes as time goes by. The latter is the reason why most GDM approaches aims at modeling the time-averaged gas distribution (Lilienthal, Reggente, Trincavelli, Blanco, & Gonzalez-Jimenez, 2009; Loutfi, Coradeschi, Lilienthal, & Gonzalez-Jimenez, 2008; Stachniss, Plagemann, & Lilienthal, 2009), being the works presented in (Asadi, Pashami, Loutfi, Lilienthal, & Gouma, 2011; Marjovi & Marques, 2014; Monroy, Blanco, & Gonzalez-Jimenez, 2016) the only notable exceptions.

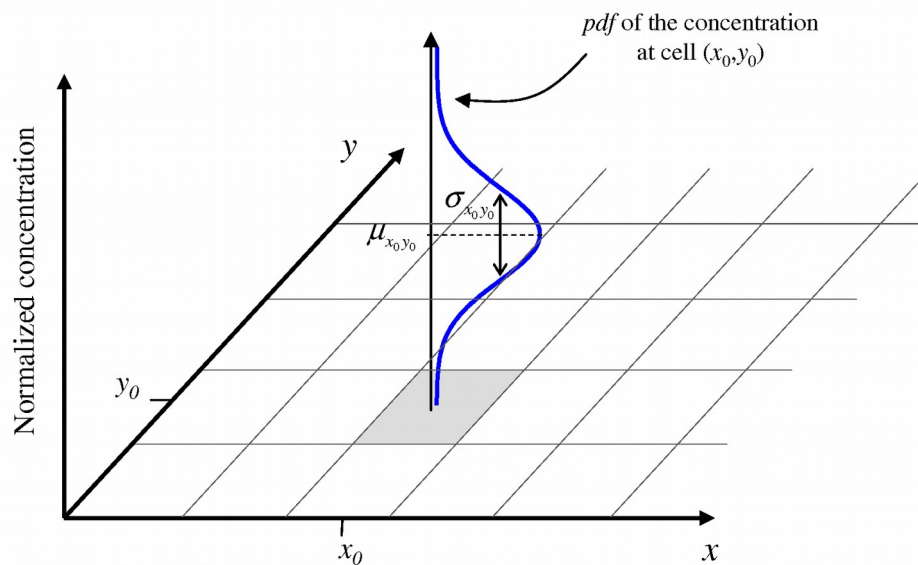


Figure 3. (A) The 2D map is commonly represented by a lattice where each cell keeps the estimate of gas concentration by means of a probability density function, represented here as a Gaussian density in the vertical axis (From (Blanco, Monroy, Gonzalez-Jimenez, & Lilienthal, 2013)).

It is the task of a GDM algorithm to extrapolate sparse measurements, both spatially and temporally, to obtain an estimation of the gas dispersal for the entire environment. Several efforts addressing this problem have been proposed in the robotics literature. Farrell et al., (Farrell, Pang, & Li, 2003) presented a hidden Markov model based approach to estimate the location of odor source based on mapping the plume. Marques et al. (Marques, Martins, & de Almeida, 2005) proposed a mapping methodology based on neural network regression and an advection-diffusion model by means of a reduced order Kalman filter. Lilienthal and Duckett (Lilienthal & Duckett, 2004) presented a grid-mapping technique based on Gaussian density functions, modeling the likelihood of each observation in the grid as a decreasing Normal distribution with respect to the distance from the point of measurement. This method was later extended for the case of multiple odor sources (Loutfi et al., 2008) and to the three-dimensional case (Reggente, Lilienthal, Pardo, & Sberveglieri, 2009). It was further shown how gas distribution mapping

methods can be embedded into a Blackwellized particle filter to account for the uncertainty about the position of the robot (Lilienthal, Loutfi, Blanco, Galindo, & Gonzalez-Jimenez, 2007).

Stressing the importance that probability and uncertainty have on any mobile robotic system, recent approaches provide in addition to the most-likely value of the gas distribution, an estimate of the associated uncertainty (via a variance value as illustrated in Figure 4). Stachniss et al. (Stachniss et al., 2009) proposed an approach using Gaussian process mixture models (GPM), treating gas distribution modeling as a regression problem. The components of the mixture model and the gating function, which decides to what component a data point belongs, were learned using Expectation Maximization (EM). At the same time, in (Lilienthal, Reggente, Trincavelli, Blanco, & Gonzalez-Jimenez, 2009), Lilienthal et al. carried out two parallel estimation processes, one for the mean and another for the variance, understanding the latter as the variability of the gas readings, not the uncertainty in the estimation which is the standard in probabilistic estimators. Results demonstrated that although providing similar maps to previous approaches, this method had the advantage of scaling better to larger training datasets and to possess a simpler learning procedure. In (Blanco et al., 2013), an approach to obtain the variance of each map cell is proposed employing a sparsified Kalman filter.

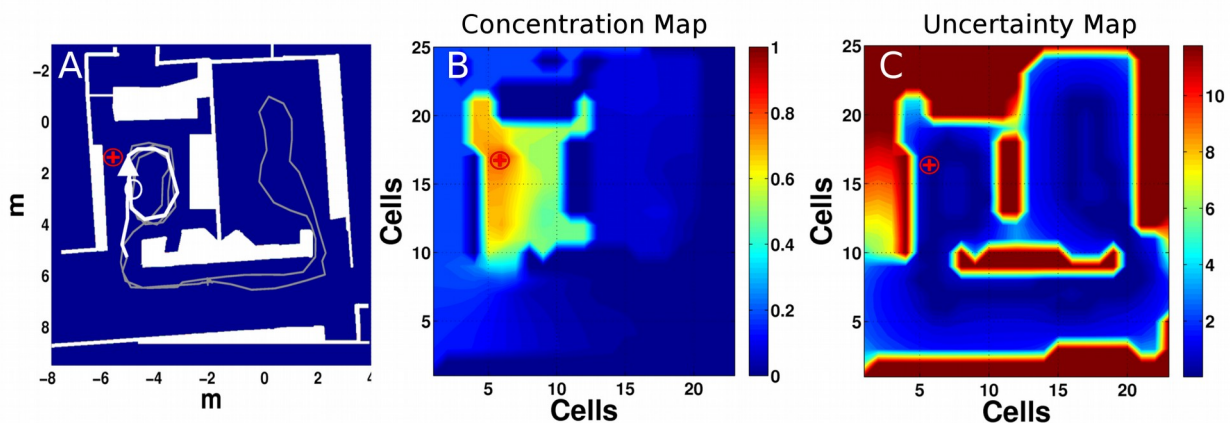


Figure 4. Example of a gas distribution map generated by a mobile robot. (A) Occupancy map of the environment (white represents obstacles and the source location is depicted as a cross inscribed within a circle) and robot path during the inspection (white-solid line). (B) Map of the estimated gas concentration and (C) associated uncertainty.(Adapted from (Monroy, Blanco, et al., 2016)).

Exploiting the availability of other sensors onboard the robot, some works have considered the presence of obstacles in the environment (Monroy, Blanco, et al., 2016), introduced wind flow measurements as secondary variables (Reggente & Lilienthal, 2010), and even considered the modeling of homologous wind maps to exploit the strong correlation between gas dispersion and wind flow conditions (Monroy, Jaimez, & Gonzalez-Jimenez, 2017). With respect the number of robots, it is common practice to face GDM with a swarm of robots (Marjovi & Marques, 2014; Nguyen, Kodagoda, Ranasinghe, & Dissanayake, 2014). This approach enables measuring multiple locations simultaneously, but introduces the problems of cross-calibration between the different e-noses, and the communication between the robots in the swarm. These problems are also shared by applications that mount multiple e-noses on other mobile platforms, such as buses (Hasenfratz, 2015), or bikes (Zappi et al., 2012) for creating pollution maps.

Up to date multiple approaches based on different mathematical and statistical models have been presented. Yet, a key hurdle to provide a formal and serious comparison among them is the lack of experimental datasets with ground truth. This is one of the main limitations for the development of precise and trustable GDM algorithms in real robots. Waiting for a breakthrough in the chemical sensing technology that could provide such ground truth, the only intermediate solution is to employ computational fluid dynamic tools which, not modeling whole the dispersion phenomena, allow us to gather reasonable accurate simulated data with ground truth.

GAS SOURCE LOCALIZATION

Gas source localization is likely the most studied research area and direct application of an olfactory mobile robot. Traditionally, it has been divided into three stages: first, explore the environment looking for the presence of a chemical release, then search for the source guided by chemical and other sensing stimuli, and finally the so called source declaration, that is, verification of the identified source location. The first stage can be considered a trigger event, not being usually carried as an active stage, but run on the background while the robot is performing other non-related olfaction operations such as patrolling, exploration, delivering, etc. If while performing these tasks, the e-nose on-board the robot detects an abnormal concentration level, then the gas source localization task is triggered and the search process begin. Therefore, the rest of this section will focus on the other two stages, the search and declaration of a gas source. More detailed information can be found in the review (Kowadlo & Russell, 2008).

Source Search

This stage involves searching of the gas release point, primarily relying on the chemical sensed data, but also on the wind flow or the objects and structure of the scenario. The success of this stage heavily relies on how well the given algorithm adjust itself to the environmental conditions, which determine the way in which odor is dispersed. In this sense, gas source localization strategies can be classified into those designed to work under the presence of a chemical plume, also known as plume tracking strategies, and those which do not rely on the existence of a well formed, downwind plume.

Plume Tracking

At medium Reynolds values, odor dispersal occurs mainly through carriage by the background fluid currents (advection), causing an odor plume to form downflow of the source (Kowadlo & Russell, 2008). In most real scenarios, this plume is not straight and continuous, but given the time-varying nature of flow fields and the predominance of turbulence over diffusion, plumes tend to meander, become patchy and, to a far lesser extent, spread out. This results in peak concentration values much higher than the average, and fluctuations in the instantaneous gradients in magnitude and direction. Furthermore, the plume structure can even change if the direction of air or water flow shifts considerably. Therefore, occasional failures are almost inevitable in the tracking of plumes (Pearce et al., 2006), being a key for success not only the track of the plume but also the plume recovery mechanisms to relocate the lost plume in case of failure.

As in the case of gas distribution mapping, research on plume tracking robots started with pure chemotactic approaches (Kazadi, Goodman, Tsikata, Green, & Lin, 2000; Menzel & Goschnick, 2000). They involve taking measurements of the chemical concentration at more than one spatially separated position, and determining the chemical gradient, which is used to move towards the source (see Figure 5). In most occasions, algorithms for searching for an odor source are based on local sensing and the reactive

behaviors of microbes, insects, or crustaceans. Such strategies involve tracking the plume along its entire length, which can be a limitation as it is time consuming and may not always be possible. Proposed strategies include Braitenberg approaches (Lilienthal & Duckett, 2003a; Russell, 2003), where a pair of bilateral chemical sensors, each directly controlling the speed of a wheel, either the opposite wheel in cross-coupling, or the wheel on the same side, are used to reach the source; Algorithms based on *E. coli* bacteria (Marques, Nunes, & de Almeida, 2002), rooted in gradient navigation through the plume; and other methods, like in (Ishida, Zhu, Johansson, & Moriizumi, 2004), exploited the airflow obstructions generated by the robot shape, and the consequent disparity between the responses of upwind and downwind sensors, to determine the moving direction. Experimental results have demonstrated that pure chemotactic approaches are relatively ineffective under real conditions where turbulence dominates, attributing their low success rate to the susceptibility of the algorithms to rapid fluctuations in the chemical concentration and the fact that the concentration gradient along the plume centerline is extremely small except in the vicinity of the source.

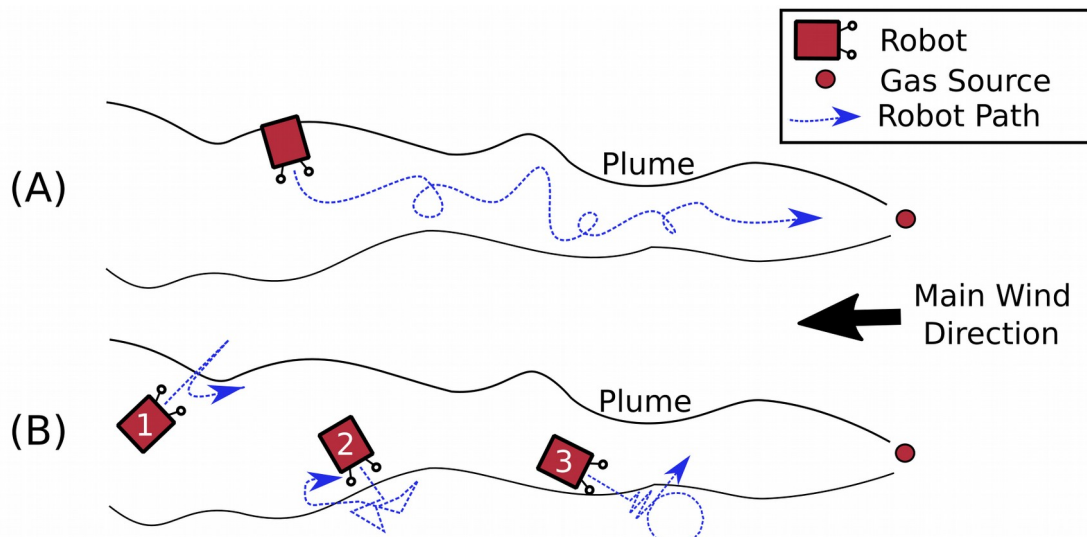


Figure 5. Illustration of chemotactic plume tracking approaches. (A) Navigation based on concentration gradients detected by comparison of the left and right chemical sensor outputs. (B) Three different plume recovery algorithms in case of lost. Robot 1 is programmed to back up when neither sensor detects chemical. Robot 2 performs random walk. Robot 3 mimics the behavior of a male silkworm moth. When one of the sensors is stimulated, the robot surges in that direction to track a plume. When the chemical signal is lost, the robot performs zigzag walk and circling to relocate the lost plume. (Adapted from (Pearce et al., 2006)).

Performance was then improved by combining chemotaxis with anemotaxis, exploiting the strong directional cue that the flow direction brings when acting under turbulent flows. Several methods have been proposed to exploit information from chemical concentration and fluid flow measurements (anemometric data), among them is the dung beetle or zigzag method, which involves moving upwind within the odor plume in a zigzagging fashion (see Figure 6A). Each time the plume boundary is encountered, the robot turns back into the plume. Reported implementations include that in (Ishida et al., 1999), which employed a basic “odor probe” composed of four pairs of a semiconductor gas sensor and a hot wire anemometer, each pair spaced 90° with respect the other, (Farrell, Pang, & Li, 2005) for

underwater robots, or (Russell, 2006) for the case of 3D. Other approaches exploiting anemotactic information are the plume-center upwind search (Ishida, Nakayama, Nakamoto, & Moriizumi, 2005; Marques, Almeida, & de Almeida, 2003) or the silkworm moth strategy, also known as the surge-cast algorithm (Lochmatter & Martinoli, 2009b). The former involves moving towards the center of the plume whilst tracking upwind, assuming that higher concentrations are likely to be found at the plume centerline. The latter is based on the studied behavior of how male silkworm moths locate female mates by tracking a pheromone release. In a nutshell, a robot in the plume moves straight upwind until it loses the plume (surge phase), then, it tries to reacquire the plume by moving cross-wind (cast phase), first on one side and then on the other (see Figure 6B). Different versions of this behavior have been presented both with procedural algorithms, and with neural networks (Pyk et al., 2006).

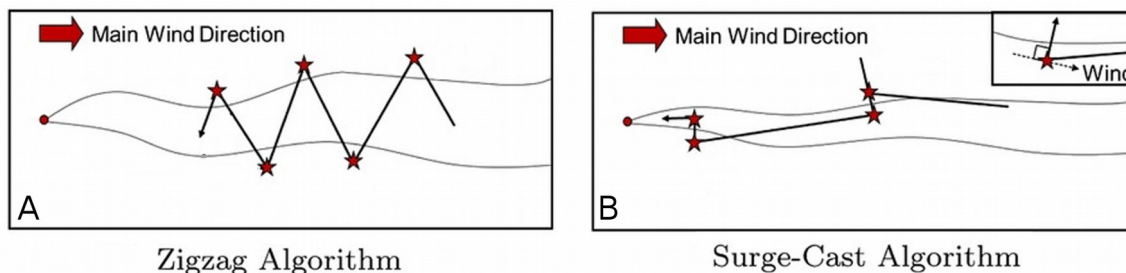


Figure 6. Illustration of (A) the zigzag algorithm (Ishida et al., 1994) and (B) the surge-cast algorithm (Lochmatter & Martinoli, 2009b). The robot continuously measures the gas concentration, and at some points (indicated by stars) also the wind direction. (Adapted from (Neumann, Hernandez-Bennetts, Lilienthal, Bartholmai, & Schiller, 2013)).

As reported in (Lochmatter & Martinoli, 2009a), the main drawback of these anemotactic strategies is the fact that under realistic, turbulent environments, a great difficulty exists in accurately determining the wind flow direction. The latter entails, in most occasions, a major impact on the success rate when compared with laboratory results. In addition, obstacles will not only negatively influence the performance, but require, in many cases, to substantially modify the algorithm (Lochmatter, Heiniger, Martinoli, Pardo, & Sberveglieri, 2009).

Turbulence Dominated Search

In most real environments, the strong predominance of turbulence as the dispersal mechanism, together with the presence of obstacles, lead to chaotic dispersion patterns where the chemical downwind plume breaks down into intermittent gas patches. Moreover, for indoor scenarios, the low strength of wind flows does not guarantee the formation of chemical plumes, being the movement of other entities (e.g. people, or the own robot) responsible of the chaotic dispersion of the gases. This entails that most plume tracking algorithms are unable to localize the source, as there is not such a thing as a chemical plume to follow.

Researchers have attempted to overcome this limitation by developing systems that go beyond purely reactive control, for example by exploiting other information sources available on the mobile robot. One of the first alternatives to appear was the combination of traditional strategies with vision based systems. This approach enables robots to identify candidates from a distance, thus dramatically diminishing the effective search space and greatly enhancing the ability to locate an odor source when a downwind plume is not well formed or even inexistent. Yet, only very basic algorithms have been proposed so far (Ishida,

Tanaka, Taniguchi, & Moriizumi, 2004; Loutfi, Coradeschi, Karlsson, & Broxvall, 2004), most of them relaying on strong assumptions about knowledge of the source shape or color, for detection of the visual candidates.

Moreover, some engineered plume-tracing strategies have also been presented, such as fluxotaxis (Zarzhitsky, Spears, Thayer, & Spears, 2004), a multirobot based approach in which computational fluid dynamics techniques are applied, infotaxis (Vergassola, Villermaux, & Shraiman, 2007) a gradient-free method exploiting the expected entropy of future samples to guide the robot search, or the SPIRAL algorithm (Ferri et al., 2009), a source location strategy for indoor environments with no strong airflows (see Figure 7). More recently, and facing more challenging environmental conditions such as time-varying airflows, Li et al proposed a novel probabilistic approach based on a particle filter (J. G. Li, Meng, Wang, & Zeng, 2011). Their main contribution was the estimation of the chemical source location while the robot performs exploratory behaviors, not necessarily requiring it to navigate towards it. In this line, Ping et al proposed a behavior-action based method (Ping, Xiao-fang, & Ai-dong, 2014), combining multiple search strategies with visual recognition, and in (Hernandez-Bennetts, Schaffernicht, Stoyanov, Lilienthal, & Trincavelli, 2014) and (Bonow & Kroll, 2013), the authors proposed the use of a TDLAS range gas sensor to localize a gas source by applying tomography principles.

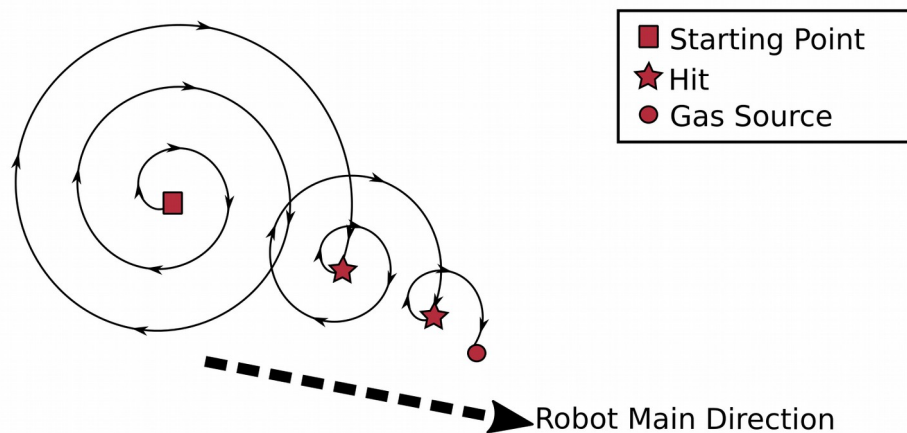


Figure 7. Illustration of the SPIRAL algorithm for gas source localization. The robot performs spiral movements, stopping to sample the gas concentration. If current measurements suggest that the robot is closer to the source (referred as a hit), it starts a new spiral movement. (Adapted from (Ferri et al., 2009)).

Finally, as introduced in previous sections, gas distribution mapping techniques have also been proposed to pinpoint the location of one or multiple chemical sources (Lilienthal et al., 2009; Monroy, Blanco, et al., 2016). These generic methods do not rely on the presence of a plume, neither on strong assumptions about the environmental conditions, however, their limitation resides in the time necessary to sweep the entire environment, and their bad scalability as the environment enlarges.

Source Declaration

The declaration of the chemical source corresponds to the last phase of the gas source localization task. Its purpose is to inspect the candidate locations provided by the search algorithm, and to verify the presence of the gas source. In many cases, this task is relegated to a human operator, which analyzing the

data offered by the robot (e.g. the robot path followed during the search stage, the gas distribution map created, or just the current gas and wind measurements) is in charge of declaring the gas source location, or a failure in the search stage. Yet, different approaches have been proposed to declare the gas source location autonomously, in most occasions derived on the basis of empirical studies.

Initial works based source declaration on the intuitive fact that gas concentration in the vicinity of the gas source should be higher. Approaches like (Grasso & Atema, 2002) proposed heuristic strategies based on gas sensor saturation over empirically set thresholds, while Cowen & Ward (Cowen & Ward, 2002) sharpen the declaration by comparing the chemical concentration at different heights. Hayes et al. (Hayes, Martinoli, & Goodman, 2002) mentioned a source declaration method which identified the source by detecting a series of contiguous odor hits, provided that such frequency of odor patches is likely to occur only near the source.

More sophisticated methods based on machine learning were proposed to improve the declaration of the gas source under more realistic environments. In (Weissburg et al., 2002) the authors based the declaration of the gas source attending to the studied chemical patterns a gas source generates, while in (Lilienthal et al., 2004) the declaration was approached as a classification problem, using neural networks and support vector machines. As reported in (Cabrita & Marques, 2013), the problem with these and similar strategies is the need of a training phase, and the assumption that the source characteristics during training would be similar to the odor sources found during normal operation. More general approaches, resorting to concentration gridmaps to achieve odor source declaration, were presented in (Lilienthal & Duckett, 2003b; Marques, Nunes, & De Almeida, 2003). Later, Li (W. Li, 2006) conducted experiments on underwater vehicles, constructing a source identification zone based on chemical detection points, and more recently (J.-G. Li, Meng, Wang, & Zeng, 2010), proposing a particle filter approach to locate and declare the gas source. Similarly, in (Neumann et al., 2013) the authors presented a novel pseudo-gradient-based plume tracking algorithm and a particle filter-based source declaration approach, testing the proposal with a gas-sensitive micro-drone.

Recent approaches like (Cabrita & Marques, 2013; Wang et al., 2016), have tackled the problem from a multi-robot approach and mass flux divergence theory, relaying in the simultaneous measurement of gas concentration and fluid flow at different locations of the environment to analyze the presence of sources.

CONCLUDING REMARKS

Gas sensitive mobile robots are not yet a reality. Most of the works mentioned through this chapter present only simulations or laboratory-based experimentation, where some control over the environmental conditions and the chemical sensors is performed. Development of chemical sensors designed for mobile robots is indeed a necessary subject for future work. More robust and efficient sensors are needed to overcome limitations such as the long response times, ageing or drift, drawbacks that hinder gas sensitive mobile robots to be deployed in real world applications.

Besides the limitations imposed by technology, that will hopefully banish with time, future work is needed to develop design strategies which enable a mobile robot with the capabilities to detect, recognize and locate chemical releases, to be useful in a variety of scenarios such as homes, manufactures or emergency areas.

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